Chasing the Tesla Standard: Predicting Battery Electric Vehicle Sales amidst Increasing Competitive Pressures

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ABSTRACT

Tesla has been a market leader in Battery Electric Vehicle (BEV) capabilities—boasting an EPA estimated travel range of 265 miles. Still, mass-market BEV manufacturers have been able to sell cars with a lower range of approximately 87 miles without having to make significant upgrades to their capacity. This is because Tesla vehicles—though powerful—are above the price point of the typical consumer. But in the next few years—anticipating Tesla's release of an equally powerful mass-market vehicle—companies are preparing to release their next generation of BEVs. Recently, Chevy announced their next generation of BEVs will have a 200 mile travel capacity—which can be seen as an effort to compete with Tesla's mass market vehicle. Based on this evidence, this paper examines the effect of travel range on sales of battery electric vehicles. Using sales data from hybridcars.com, I conducted an econometric analysis of factors that affect BEV adoption using a multivariate regression model with both fixed variable effects and fixed time effects. The main dependent variable of interest was monthly vehicle sales while the main independent variable of interest was travel range. Other independent variables such as gasoline prices and vehicle prices were included to help isolate the effect that travel range has on BEV sales. Through various iterations of the multivariate regression model, the linear coefficient of travel range regressed on sales remained positive and statistically significant ($p<0.01$) with a with an approximate 5.4-5.6% increase for every additional mile of range.

KEYWORDS

Tesla Model III, Travel Range, Econometric Analysis, Travel Range Anxiety, Vehicle Adoption

INTRODUCTION

Electric vehicles are often seen as a cleaner alternative to fuel-based vehicles as they tend to have lower carbon emissions. While there are a variety of electric vehicles, Battery Electric Vehicles (BEV) have the greatest potential for carbon independence as they are completely battery powered. However, there are a number of drawbacks that leave BEVs infeasible for mass market penetration such as limited travel range, long charging times, and a lack of charging infrastructure. Tesla, a BEV manufacturer, has made efforts to curb these disadvantages through technological innovations and implementation of their own charging stations. But, where they really pose a competitive advantage in the BEV industry is in their travel range. Compared to the industry average range of 87 to 124 miles, Tesla boasts a much larger range of 265 miles (Hardman 2015, Electrification Coalition 2012). Until recently, Tesla vehicles have largely been inaccessible to the mass-market due to their high prices. This changed with the announcement of the intended release of the Model III, a $35,000 vehicle with a 215 mile range (teslamotors.com 2016). A more affordable class of their vehicles could have large implications for the EV market, on the whole. Tesla's competitive advantage in travel range paired with their new mass-market appeal will force other automakers to make comparable improvements to compete or risk losing market share.

Prior to Tesla's announcement, Chevrolet announced their plans to release their next generation BEV—the Bolt—which is expected to have a 200 mile range starting at $37,500 (hybridcars.com 2016). This is significant as Chevrolet's previous BEV—the Spark—had an 84 mile capacity. To drastically increase their travel range from 84 to 200 miles is somewhat arbitrary without context. However, Tesla's mass-market Model III has been a publicly known part of their business plan for many years now (Musk 2006). As a result, despite the Bolt's earlier announcement and release date, Chevrolet's rapid technological improvements can be seen a direct response to the upcoming Tesla Model III. As Chevrolet leads the charge in competing with Tesla on travel range, this leaves speculation on the market as a whole. Will other automakers make similar improvements to their BEVs?

If other automakers were to also increase the travel range of their BEVs, this could have a significant impact on the BEV industry due to changes in consumer sentiment. According to the Electrification Coalition, 68% of Americans travel less than 40 miles per day (Electrification

Coalition, 2013). At this level of driving demand, BEVs in their current state should suffice for the majority of the public. Still, consumers cite travel range as one of the main reasons for not purchasing a BEV (Electrification Coalition 2013). This may be due to the fear of being stranded with little to no charge—which is typically referred to as range anxiety (Nillson 2011). Range anxiety can be partially alleviated through measures like increased availability of charging infrastructure, free roadside assistance, and remote access to the status of the car (Nillson 2011). However, because data shows that the onset of range anxiety tends to occur when the charge falls below 50%, it can be addressed by simply increasing the travel range (Caroll 2010). With rapid improvements in travel range imminent, consumers may become more inclined to switch over to BEVs.

While consumer preferences for travel range have been well studied, information about its market influence is limited. Previous studies have touched on the subject of travel range without it being the main focus. For example, one study was conducted via survey to find factors that are most influential in a consumer's purchasing decision (Egbue and Long 2012). As travel range was identified as the biggest concern, its market impact is not quantified. In an econometric study, factors such as incentives, fuel prices, income, and vehicle price were used to study their market impact—but lacked analysis on travel range (Sierzchula et al. 2014). Contrastingly, this study attempts to discover how improvements in travel range can affect BEV sales in the US market.

Using a simple multi-variable fixed effects regression, this study estimates the linear relationship between travel range and sales of BEVs. In order to accomplish this, other exogenous variables affecting the sales of BEVs must be incorporated into this model to isolate the true effect of travel range on sales. Within the scope of this study, gasoline prices and vehicle prices are identified as the other main contributors to the sale of a BEV. Under general economic intuition, vehicle pricing is identified as a factor because as prices increase, we should expect to see quantity sold to decline. This relationship is enforced with Egbue and Long's study on consumer attitudes where they find that cost is the second most important factor when considering BEV adoption (Egbue and Long 2012). Gasoline prices are included into the study as they are also influential in the decision making process. As gas prices increase, the operational costs of conventional vehicles also increase. When conventional vehicles are costlier to operate, consumers have more incentive to switch to alternatively-fueled vehicles like a BEV. This relationship can be observed in the hybrid electric vehicle market where gas prices were positively correlated with sales (Gallagher and Muehlegger 2011). Additionally, fixed entity effects are included to account for inherent differences in automakers. For example, some models like the Nissan Leaf have more sales due to its earlier release while the Smart Car may have lower sales due to its lower perceived vehicle safety. Lastly, time-fixed effects account for conditions that may vary across time such as macro-economic conditions. When the U.S. economy is not doing as well, vehicle sales may decline as well. The strength and directions of these variables' relationship to sales will allow me to estimate the effects industry improvements.

BACKGROUND

Electric Vehicles (EVs) come in many forms—each varying in the amount that they rely on an electric battery. A Hybrid Electric Vehicle (HEV) captures the energy normally lost to braking but still heavily relies on its internal combustion engine (Pappas 2014). While HEVs rely greatly on their combustion engine, a Plug-In Hybrid Vehicle (PHEV) is less gasoline dependent. A PHEV can plug into an outlet to charge a battery, and typically runs about 40 miles before switching to its gasoline-powered internal combustion engine (Pappas 2014). Finally, purely electric vehicles—known as Battery Electric Vehicles (BEV)—have the longest battery powered travel capacity of the suite of EVs, but still do not have the same travel range of combustion engines. Due to their compatibility with current gasoline infrastructure, HEVs have been the most commercially successful electric vehicle since the invention of the Toyota Prius in 1997 (Matulka 2014).

While HEVs are the most popular of the electric vehicles, they are still vastly out-numbered by traditional internal combustion vehicles (ICVs). As of October 2015, hybrid electric vehicle sales constituted a 2.25% share of all light duty vehicles --or about 320,000 units (Zhou 2015). Hybrid Electric Vehicle sales have been on the rise since 1999. Their market share of all new, light-duty vehicle sales rose to a peak of about 3.2% in 2013 (Zhou 2015). However, a paper on the consumer response to gasoline pricing reports that the elasticity of driving demand when compared to the price of gasoline is approximately -.15 (Gillingham 2011). As a result, the decline in gasoline prices since 2013 may explain the decline in HEV sales in recent years (Energy Information Administration 2015). PHEVs constitute smaller fraction of total vehicle sales, amounting to 0.05% of all registered vehicles in 2013 (Chase and McFarland 2014). As these numbers are low, local and national governments have implemented a number of subsidy programs to encourage use of battery powered vehicles. For example, the Federal government offers a base-line subsidy of $2,500 to consumers that increases with battery capacity up to a maximum of $7,500 to (Chase and McFarland 2014). While the Federal government enacted its policy as a recession recovery method, California has offered up to $5,000 in payments as a part of its Clean Vehicle Rebate Project (Center for Sustainable Energy 2015). In a 2013 projection generated by Price Waterhouse Coopers, plug-in electric vehicles (encompasses both BEVs and PHEVs) were expected to grow to 3% of all vehicle sales by the year 2020 (Electrification Coalition 2013). This is a substantial increase from 0.4% in 2012, 0.6% in 2013, and 0.7% in 2014 (Chase and McFarland 2014).

Of the two categories of plug-in electric vehicles, BEVs have shown more potential for mass-market penetration than PHEVs despite their drawbacks. Their limited travel capacity, long charging times, and a lack of widespread infrastructure make the product appear infeasible for mass market penetration. However, their sales figures when compared to comparable technologies suggest this is not the case. In 2012, BEVs constituted a 0.096% share of the total vehicle market (Eichberger 2014). In 2013, that share grew to 0.31% (Eichberger 2014). Comparatively, PHEVs only grew from 0.26% to 0.31% in this duration (Eichberger 2014). Of the BEVs designed for mass market use, the Nissan Leaf stands out as a market leader. The 2013 Nissan Leaf has an 84 mile capacity (standard gasoline vehicles range from 250-350 miles), a charging time as high as 21 hours, and sell for approximately $29,650 (Cobb 2013). Despite drawbacks in travel range and refueling time, when comparing the growth rate of BEVs to PHEVs, BEV's independence from gasoline may play a key part to their success.

Tesla, a competitor to vehicles like the Nissan Leaf, is operating with a competitively better product in terms of travel range and charging time. As of March of 2016 they have achieved monthly unit sales that exceed the Leaf by 2,000 units, selling primarily to wealthier consumers with the Model S—which base price starts at $69,900 (hybridcars.com 2015). With an EPA rated mile capacity of 265 miles, the Model S has a travel capacity three times greater than the standard BEV (Department of Energy 2012). In addition, all Tesla vehicles are equipped to handle Direct-Current (DC) charging which provides 120kW and can provide approximately a

50% charge to vehicles in 30 minutes whereas other vehicles may require additional payments (Hardman 2015).

Tesla is preparing to release an affordable, mass-market electric vehicle with capabilities similar to the Model S. Their superior technology, soon to be offered at a lower price, has many implications for the BEV market. The Model III grants consumers greater access to Tesla vehicles and places competitive pressures on other automakers. If Tesla were able to release their mass-market vehicle without response from competitors, it would have a superior product with similar pricing. As a result, they could potentially engulf the entirety of the BEV market. However, this is unlikely to be the case.

Review of Extant Models

Studies on consumer adoption of BEVs have largely been limited to surveys on preferences. In a 2013 review of existing studies on EV adoption, Al-Alawi and Bradley categorize three experiment types: Agent-Based, Consumer Choice, and Diffusion Rate. Agent-Based models (ABM) are characterized by a computer simulation of interactions between different agents that have different demographics and preferences. The ABM is advantageous in that it can use agent specific characteristics, but has complexity that is hard to validate (Al-Alawi and Bradley 2013). Consumer choice models are less complex and project future behavior through probabilistic preference. Typically these are known as discrete choice models and logit models. They can be powerful when there is a wealth of historical data but current literature typically derives it from hypothesis or survey data (Al-Alawi and Bradley 2013). Finally Diffusion Rate Modeling predicts the rate at which a new technology is adopted by the market. These models typically include an S-shaped adoption curve and a classification of adopters such as early adopters, early majority, late majority, and laggards. While these models are easy to implement, it is hard to estimate peak level of sales and to account for existing products (Al-Alawi and Bradley 2013).

BEV adoption studies with OLS Regression Models as the focal point are less common due to limited data sets. As a result, comparable studies to this one can be found in analyses of different countries and similar technologies. In a 2013 study on HEV sales, an econometric regression is conducted to understand how monthly vehicle sales are affected by the implementation of different government incentives (Jenn et al. 2013). Using monthly vehicle sales the dependent variable, Jenn (2013) analyzes correlations with explanatory variables such as government incentives like cash for clunkers, advertising campaigns, and macroeconomic factors like gasoline prices. The regression equation below represents their OLS estimation where $S_{i,t}$ represents monthly vehicle sales by model, $EPACT_{i,t}$ is the dollar incentive for the vehicle model in the time period, $x_{i,t}$ is a control variable, and u_i is unobserved car characteristics.

$$\ln(S_{i,t})=\alpha+\pi\ln(S_{i,t-1})+\beta(EPACT_{i,t})+\gamma(x_{i,t})+u_i+\varepsilon_{i,t}$$

Another OLS study was conducted with data from 30 different countries but only used data in the year 2012 (Sierzchula et al. 2014). Rather than using panel data, this study analyzes financial incentives and socioeconomic factors that vary with location. On the left side of the OLS regression equation below is the dependent variable is the log of the market share that BEVs hold in country (i). On the right side are the dependent variables consisting of incentives and socioeconomic factors in country (i).

$$log\_MarShr_i = \alpha + \beta_1 Incentive_i + \beta_2 Urbandensity_i + \beta_3 Education_i + \beta_4 Env_i + \beta_5 Fuel_i$$
$$+\beta_6 ChgInf_i + \beta_7 Elec + \beta_8 PerCapVehicles + \beta_9 EV\_Price + \beta_{10} Availability + \beta_{11} Introduction + \beta_{12} HQ + \varepsilon_i$$

Study Model

The model used to analyze the effect of travel range on BEV sales reflects similar methods listed above. To estimate the effect of travel range on BEV sales, I used an Ordinary Least Square (OLS) regression of sales on multiple explanatory variables. The study is similar to both Jenn's (2013) model in that it uses panel data and the log of sales as the independent variable while sharing some explanatory variables with Sierzchula's (2014) model. By using the log of sales, this gives an approximation for the percentage increase in sales as opposed to nominal increases. However, this study differs by using time-fixed effects to account for unobservable time variant factors. Listed below is the OLS model used to isolate the effect of travel range on sales and a description of all the variables.

$$\ln(S_{it}) = \beta_0 + \beta_1 X_{it} + \beta_2 Y_t + \beta_3 Z_{it} + \alpha_{it} + F_i + T_t + \varepsilon_{it}$$

Table 1. Variable Descriptions. A list of descriptions for all the variables used in OLS Model

Variable	Description
S_{it}	Sales of Car Model (i) in time period (t) in units
β_0	Intercept (Baseline level of BEV adoption)
β_1	Effect of Travel Range on Sales
X_{it}	Travel Range of Car Model (i) in time period (t) in miles
β_2	Effect of Gasoline Prices on Sales
Y_t	Average US Gasoline Price in time period (t) in $
β_3	Effect of Vehicle Price on Sales
Z_{it}	Price of Car Model (i) in time period (t) in $
α_{it}	Bivariate dummy variable to identify when car′s first three months on sale
F_i	Fixed Entity Effect of Car Model on Sales
T_t	Monthly Time Fixed Effect on Sales
ε_{it}	Error Term

From this regression output, I will use the linear relationship between travel range and log of sales to estimate the percentage increase in sales.

METHODOLOGY

Data Collection

I collected data on four different variables—BEV sales, travel range, vehicle price, and gasoline prices—up until March of 2016. Because discovering travel range's relationship to sales is the primary goal of this study, the panel data revolved around available sales information. BEV sales data only dates back a few years and as a result, annual data is not conducive for statistical tests. However, monthly figures were publicly available and effectively increased the sample size. In Jenn's (2013) regression analysis on HEV sales, monthly sales were used as opposed to annual sales. Monthly figures also provide other advantages such as being able to account for more fluctuation in travel range, gas prices, and vehicle prices. Using this intuition, monthly figures were used instead of annual figures.

BEV Sales

Similar to Jenn's study on HEV adoption, I sourced monthly BEV sales data listed on hybridcars.com (Jenn et al. 2013). Hybridcars.com is a source that has been cited by the U.S. Department of Energy and is a reputable source for these figures.

BEV Travel Range

To collect data on travel range, I used the Department of Energy's fueleconomy.gov to retrieve the BEV's EPA estimated ranges. While travel ranges may vary between websites, using the EPA estimated range keeps the standard relatively consistent. The listed travel ranges are based on automaker's submitted test results which can result in some bias (EPA 2015). However, the EPA may conduct its own tests and change the listed range if there are discrepancies (EPA 2015). This keeps the standard across automakers relatively consistent and reflects what the consumer would encounter in a market situation.

Vehicle Price

To further isolate the effect of travel range on sales, I sourced vehicle prices from the Department of Energy's fueleconomy.gov. If multiple vehicle prices were available for the model, a simple arithmetic average was calculated. Because vehicle prices change between years, I populated my dataset according to their release date. If a release date was accessible, I would change the vehicle price starting that month. However, if a release date was not listed, I listed the new price exactly 12 months after the previous model year was released.

Gasoline Price

As gasoline prices play a role in consumer's perceptions of electric vehicles, I sourced information on prices from the energy information administration (EIA). Gasoline prices were denominated in dollars per gallon. For each month/year that was listed, I referenced EIA and listed the average monthly gasoline prices. Average gasoline price was held consistent across vehicle models for each month.

Data Manipulation

During the data collection process, I noticed some data irregularities and accounted for these using bi-variate dummy variables and deletion. A dummy variable I generated was for the first three months of sale. If a car was in its first three months of sales, it would generate a "1" while the rest would be zero. In the first few months of sales there are shipment delays that significantly reduce the figures. At the end of 2015, both the Toyota Rav4 EV and Honda Fit EV concluded their production and their sales declined drastically. As a result, I deleted the sales data for both the Rav4 and the Fit EV after production ended.

The data was organized into panel form which contains both the vehicle model and the date. In doing so, I am able to account for differences in vehicle attributes (fixed entity effects) and time-specific conditions like macroeconomic fluctuations (time fixed effects)—both of which are non-measurable parameters. As a result, I encoded the car model variable and the date variable for Stata to interact properly. Using the encode function, I generated the variable model1 and date1 to use for regression.

Additionally, from a surface level interpretation of sales data, Tesla BEV sales appear abnormally high despite higher costs. This may be due to the fact that Tesla vehicles may be viewed as luxury vehicles as opposed to BEVs. If this is the case, consumers of the Model S are not interested in the BEV for pure functionality. As a result, a second pool of data without Tesla's sales is generated and used for analysis.

Dataset Summary

My final pool of data came down to seven variables (sales, ln sales, travel range, gas price, vehicle price, dummy variable for the first three months, vehicle model, and date) and had

438 observations. The model and date variables were not encoded for Stata to interact properly initially. Model1 and date1 were generated and encoded for Stata to run fixed time effects and time fixed effects regression. Four continuous variables (Sales, Range, Gas Price, and Price) were also included (Table 2).

Table 2. Summary Statistics. Summary statistics for complete data set. Table includes the manipulations included in Stata.

Variable	Observations	Mean	Std. Dev.	Min	Max
Model	0				
Date	0				
Sales	438	458.3174	719.7436	0	3202
Range	438	96.80594	51.09295	62	257
Gprice	438	3.108667	.6021555	1.872	3.96
Price	438	37590.36	16651.5	22995	88800
Fthree	438	.0753425	.264245	0	1
Model1	438	6.508132	3.281679	1	12
Date1	438	33.09361	18.69037	1	64
lnsales	431	4.965569	1.676143	0	8.071531

Additionally, I plotted the two main variables of interest—Sales and Travel Range—and discovered a general positive relationship (Figure 1). Within this scatterplot, there are two major clusters observable. On the left end of the graph are standard BEVs, and on the right are Tesla BEVs.

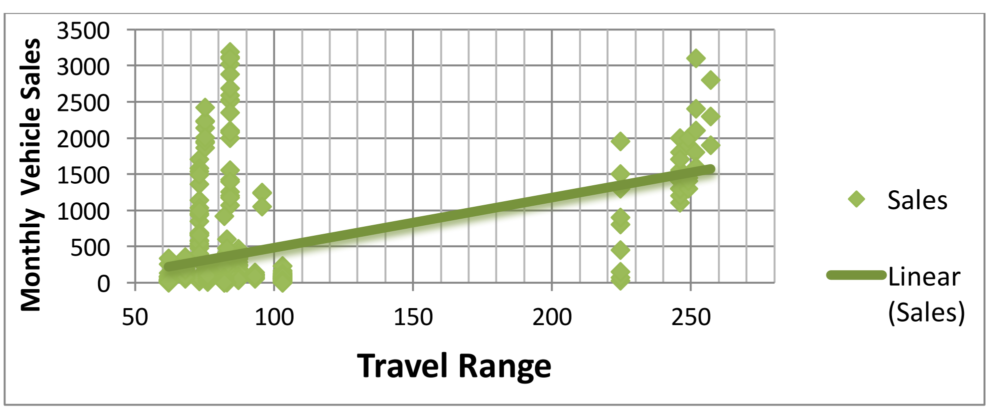

Figure 1. Sales and Range Scatterplot. Scatterplot with line of best-fit of two main variables of interest: sales and travel range.

Econometric Analysis

In order to isolate the effect of travel range (β_1) on sales (S_{it}) I ran a multivariate regression with sales as the dependent variable in Stata 13 (Statacorp 2013). I set the fixed effects (time and entity) by using the xtset function. I conducted different combinations of regressions using the xtreg function with sales as the dependent variable. For the full regression, I regressed the log of sales on travel range, price, gasoline price, first three months of sale, and included the fixed time effect and fixed entity effects. This generated regressions useful for analyzing for the effect of BEV travel range on sales. Using these procedures, I generated models useful for analyzing for the effect of BEV travel range on sales.

$$\ln{(S_{it})} = \beta_0 + \beta_1 X_{it} + \beta_2 Y_t + \beta_3 Z_{it} + \alpha_{it} + F_i + T_t + \varepsilon_{it}$$

RESULTS

Regression Results

In Model 1, I used all the collected variables to estimate the effect of travel range on BEV sales. Running the regression without the fixed effects, all the coefficients were statistically significant at a 99% confidence level *($p < 0.01$)*. Not accounting for fixed effects, for every additional mile of travel range, this would result in a 3.9% increase in sales. In addition, for every additional dollar in gasoline price we would expect a 39.8% increase and for every thousand dollar increase. In terms of vehicle price, its effect appears to equal zero. However, as noted in the non-log transformation iteration of the regression in column 1, it is lowly negative. This is consistent with the intuition that as vehicle price increase, sales would decrease. However, when time fixed effects are included, gas price and vehicle price lose their statistical significance (Model 1). As a result, the model was adjusted – resulting in Model 2.

Table 3. Model 1 Regression Output. Full Regression Model Output with varying combinations of fixed effects and time fixed effects.

	sales	lnsales	lnsales	lnsales	lnsales
range	16.663	0.039	0.060	0.054	0.043
	(10.51)**	(8.94)**	(6.21)**	(4.50)**	(9.00)**
vprice	-0.030	-0.000	0.000	0.000	-0.000
	(5.62)**	(5.70)**	(0.01)	(0.39)	(5.87)**
gprice	150.272	0.398	0.489	-1.488	1.204
	(2.93)**	(3.37)**	(6.03)**	(0.49)	(0.23)
fthree	-415.889	-1.334	-1.319	-1.158	-1.492
	(5.64)**	(5.23)**	(8.65)**	(6.16)**	(4.82)**
_cons	-472.885	2.922	-2.300	3.103	1.868
	(3.98)**	(7.75)**	(2.11)*	(0.32)	(0.11)
Entity FE	NO	NO	YES	YES	NO
Time FE	NO	NO	NO	YES	YES
R^2	0.35	0.32	0.24	0.37	0.40
N	438	431	431	431	431

* $p<0.05$; ** $p<0.01$

In order to determine which of these variables are causing the lack of statistical significance in Model 1, I ran a simple diagnostic of the full regression. By checking for the variance inflation factor for these variables, I found that the factors range and vehicle price were above the common threshold of 10 (Table 2). High levels of VIF indicate multi-collinearity and as a result, one variable must be removed. As range is the variable of interest and still statistically significant, vehicle price is removed. After removing vehicle price, VIFs return down to acceptable levels.

Table 4. VIF Output. Variance Inflation Factor output a) VIF output with range, vehicle price, gas price, and dummy variable. b) FI output without vehicle price

(a)

Variable	VIF	1/VIF
Range	11.46	.087900
VPrice	11.38	. 087258
Gprice	1.13	.881430
Fthree	1.03	.968491

(b)

Variable	**VIF**	**1/VIF**
Range	1.00	.999784
Gprice	1.03	.971801
Fthree	1.03	.971940

In Model 2, I included travel range, gas prices, and the dummy variable that indicates the first three months of distribution. Without fixed effects, only range and fthree remained statistically significant at a 99% confidence level (*p<0.01*). With the inclusion of entity fixed effects, gasoline prices became statistically significant as well. However, with the inclusion of time fixed effects, gasoline prices lost its significance again. Due to the lack of statistical significance in gasoline prices, time fixed effects appears incompatible with this gas prices. In column 5 of Model 2, the regression is run with both fixed effects without the gas price variable. In this iteration of the regression, every additional mile in range would result in a 5.6% increase in BEV sales.

Table 5. Model 2 Regression Output. Regression Model Output with varying combinations of fixed effects and time fixed effects without vehicle price.

	lnsales	lnsales	lnsales	lnsales	lnsales
range	0.015	0.060	0.056	0.016	0.056
	(11.38)**	(6.30)**	(5.15)**	(11.45)**	(5.18)**
gprice	0.193	0.490	-1.460	1.268	
	(1.65)	(6.28)**	(0.49)	(0.23)	
fthree	-1.421	-1.319	-1.171	-1.472	-1.161
	(5.39)**	(8.67)**	(6.33)**	(4.55)**	(6.32)**
Entity FE	NO	YES	YES	NO	YES
Time FE	NO	NO	YES	YES	YES
_cons	2.991	-2.297	3.138	0.778	-1.482
	(7.66)**	(2.22)*	(0.33)	(0.04)	(1.18)
R^2	0.27	0.24	0.37	0.35	0.37
N	431	431	431	431	431

* p<0.05; ** p<0.01

Using the results of the previous regression, I ran an analysis excluding Tesla BEVs (Model 3). In the initial regression in column 1, range and the fthree dummy variable are statistically significant at the 99% confidence level (*$p<0.01$*) while gas price is significant at the 95% confidence level (*$p<0.05$*). When accounting for entity fixed effects, the results of the regression appear to indicate that for every additional mile of travel range should result in a 5.6% to 6.7% increase in sales. For every dollar increase in gasoline prices, sales are expected to increase by 55%.

Table 6. Model 3 Regression Output. Regression Model Output with varying combinations of fixed effects and time fixed effects without vehicle price and excluding Tesla BEVs.

	lnsales	lnsales	lnsales	lnsales
range	0.025	0.067	0.056	0.031
	(3.71)**	(4.55)**	(3.17)**	(4.25)**
gprice	0.269	0.546		
	(2.07)*	(6.36)**		
fthree	-1.328	-1.249	-1.137	-1.561
	(4.57)**	(7.59)**	(5.63)**	(4.39)**
Entity FE	NO	YES	YES	NO
Time FE	NO	NO	YES	YES
_cons	1.950	-2.277	-0.746	3.736
	(2.68)**	(1.76)	(0.50)	(2.25)*
R^2	0.08	0.19	0.34	0.18
N	386	386	386	386

* $p<0.05$; ** $p<0.01$

DISCUSSION

The goal of this study was to confirm and isolate the effect of travel range improvements on battery electric vehicle adoption. In this aim, I conducted multi-variable regression analyses of different factors that may affect adoption of BEVs. Variables such as gasoline prices, vehicle prices, and fixed-effects were used to isolate the effect of travel range. As fixed-effects were included, some of these variables lost their statistical fit within the regression mode due to potential collinearity. However, with each additional explanatory variable (gasoline prices, vehicle prices, fixed effects) included into the regression model, the coefficient of travel range on BEV adoption became less positive. This is indicative that the cumulative effect of variables other than travel range has a negative effect on sales.

One of the hypotheses I made in this study was that gasoline prices would be positively correlated to adoption of BEVs. I reasoned that if gas prices increased, consumers would likely shy away from gasoline-dependent vehicles and embrace clean-energy alternatives, like BEVs. This along with other studies has shown that this is typically the case (Sierzchula et al. 2014). Without including fixed-effects, gasoline appeared to have a positive and statistically significant correlation with monthly BEV sales. However, once time fixed effects were included in the regression, gasoline prices lost their statistical significance ($p>0.05$). Including time fixed-effects into my regression may have introduced collinearity. As time fixed-effects accounts for variations in time, it shares a degree of correlation with monthly gasoline prices. Moreover, I used nationwide average retail prices whereas BEV consumers may be concentrated in specific regions, or they might encounter different effective gasoline prices from this average. As a result, gasoline prices' correlation with BEV adoption may have significance, but it appears to lack compatibility with a time fixed-effects regression.

Another variable that I predicted to alter the adoption rate of BEVs was the base price of the vehicle. Considering basic economic intuition, as the price of a vehicle increases, one should expect sales to decline. My regression model did yield a negative coefficient for this relationship, but this variable also lost significance and became positive when fixed variable-effects were included into the regression. Variance inflation factor analysis indicated that vehicle price had a high degree of collinearity with travel range. The collinearity between vehicle price and travel range would again indicate that this vehicle price does not fit within the regression model. This seems logical because as battery size increases, we would expect a higher inherent price of the vehicle. However, the collinearity between these two variables indicates a difficulty in conducting BEV adoption analysis. Both travel range and vehicle price are important factors that consumers consider when purchasing a BEV, but it is hard to measure their effects simultaneously. Despite this setback, consumer preference surveys can attempt to quantify their individual effects.

Finally, I predicted increases in travel range to have a positive effect on sales. Throughout the iterations of the multivariate regression, travel range consistently remained statistically significant and had a positive correlation with BEV sales. Between the iterations, the incremental effect of travel range on monthly BEV sales varied from a 1.5% to 6.5% increase in sales per additional mile in range. However, when accounting for regression iterations that include entity and time fixed-effects, the coefficient narrowed to a range of 5.4% to 5.6%. In finding the correlation between vehicle adoption and travel range, I expected to see higher BEV sales with higher battery capacity. As seen with Chevrolet's move to make a rapid increase from an 84 mile range vehicle to a 200 mile range, these competitive pressures may result in rapid improvements across the board. However, it is interesting to note that even when vehicle pricing was removed from the regression model, the coefficient of travel range versus BEV sales remained positive. This seems to indicate that the preference for higher travel ranges has greater influence on vehicle sales than negative effects of higher pricing. On a surface level extrapolation, this may indicate that current BEV customers have other motivations behind their purchases that extend beyond economic incentives.

Limitations

Deeper insights into the industry are hard to extrapolate given the extent of this study. The methods for tallying of monthly auto sales were not explicitly stated from hybridcars.com nor were they mentioned in similar sites like the Auto News Data Center. As a result, further manipulations of the data set were not possible due to this limitation. For example, if sales were sourced directly from the DMV with sale prices, further analysis of demand with relation to pricing could be estimated. In addition, the actual purchase price of the vehicle may vary depending on the add-on features, taxations, or subsidies that are applied. Therefore, assumptions made in this study—like using the lowest-listed MSRP price—were used to accommodate this limitation, but may skew the coefficients retrieved from the regression analysis. Moreover, measures such as availability of charging infrastructure were not included in the study as it is difficult to achieve accurate data due to the lack of information from private entities such as private parking structures. Lastly, this study suffers from the lack of a long time-series. Mass-market BEVs only date back a few years and major automakers are still absent from the market.

Future Directions

Further econometric studies may gain more explanatory power in predicting BEV adoption as these vehicles mature in a technological sense and gain more mass-market traction. As indicated from the results in this study, the incompatibility between travel range and vehicle prices makes it difficult to conduct a more refined econometric analysis. Consumer preference surveys that further examine these two variables may allow for more insight on their individual effects. Even within this year, pre-orders for the $35,000 Tesla Model 3 have begun (ABC News 2016). Alongside the Chevrolet Bolt, sales from the new generation of mass-market and long-distance BEVs will provide data for greater insight into the market and consumer demand for these vehicles. Additionally, this type of econometric analysis can be applied to other markets abroad or even sized down to smaller geographic regions such as the state of California. Smaller geographic regions allow for closer analysis of factors that affect BEV sales, such as being able to quantify the availability of charging infrastructure, which is difficult to accomplish in a nationwide analysis.

While the nature of this research project appears to be an attempt to look at the near future, the implications of a vastly changing vehicle network are massive. BEVs depend on different modes of energy production than conventional vehicles. As a result, knowing the rate of adoption of BEVs will allow for utilities to accurately predict the additional grid capacity needed to power these vehicles. In addition, the widespread adoption of BEVs has the potential to reduce the nation's carbon footprint by reducing America's reliance on gasoline. However, the actual benefit of BEVs depends on the energy portfolio of grid systems currently in place. Knowing the rate of BEV implementation will help determine the immediate impact of a cleaner energy portfolio on society. In general, having a more accurate forecast of BEV adoption will allow for policy leaders to make well-informed decisions that benefit the public good.

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